Reducing Process and Measurement Noise and Errors in Technical Processes and Sensors

Application of Kalman Filter

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Abstract

In this research we have demonstrated Kalman Filter (KF) that improves the quality of the measurement of sensor signal. Kalman Filter has long been used to eliminate the process error and measurement noise. Bearing in mind that almost all industrial automation and control systems are stock with process errors and measurement noises, we tried to implement Kalman Filtering algorithm to typical processes that measure the height of the water level of a tank and the angle of deviation of the wheel of a Mobile Robot (MR) from a predefined guided path. First a simulation study was conducted using the developed Kalman Filter algorithm. The algorithm was then translated and transferred to a real-word implementation domain which is an electronic computing module. While a level detector (pressure sensor) was used to sense the height of the real-time water levels under filling, dropping, both conditions, the LVDT transducer, developed in the laboratory was used to measure the angle of deviation of a MR's track in a lab room experimental setting. It was observed from the results that process error and measurement noise can be eliminated using KF. The paper systematically presents the results after reviewing the theoretic model of the KF and the application of families of KFs. We were able to reduce the errors and noise from about 15% to 5% using KF technique.

Keywords

Kalman Filter; Noise; Error; Estimation; Liner System; Sensor; Mobile Robot; Water Level Measurement

Introduction

Filtering plays a key role in most of the advanced signal processing systems, automated systems, and measuring devices such as sensors (Watzenig, Steiner, and Zangl, 2008). Most of the processes have some degree noise, disturbances, or errors due to which the outputs of the systems are not the true measurements. As a matter of fact, the performance and efficiency of the system is compromised. For example, when the measurements are needed for feedback applications, the error and noise undermine the system performance. Filters can eliminate the unwanted noise, disturbances, or errors and can provide output closer to true value. Kalman Filter (KF), developed by R. E. Kálmán, computes the process variables and measurements in a way that the estimation results with lower errors and noise in most of the cases (Kalman, 1960). Fig.1 shows the basic functioning of a KF. Kalman filter is a recursive filter that operates on the current state taking into account of previous state.

Bearing in mind that almost all industrial automation and control systems are stuck with process errors and measurement noises, we implemented Kalman Filter algorithms in two exemplar process control components: one that measure the height of the water level a simple process measuring system and the second that measure the deviation of angle to be used for feedback application. While, a level detector was used to sense the height of the real-time water level, an LVDT sensor, developed in the laboratory was used to measure the angle of deviation of a MR's track in the lab room experimental settings. It was observed from the results that process error and measurement noise can be eliminated using KF.

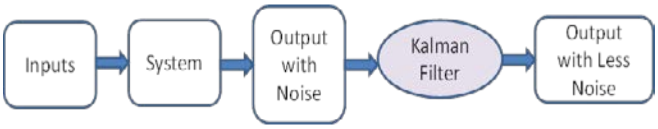


FIG. 1 USE ONLY SOLID FILL COLORS

Review on Theoretic Model of Kalman Filter

In this section a theoretic model of Kalman Filter (KF) is reviewed. The filter preferably works when the non-stationary stochastic process variable distributions are Gaussian and the noise has zero mean. If the variance is higher, the noise level will also be higher. It is assumed that the noise is white, meaning the spectral

density is constant over a wide range or alternatively, the noise has equal energy at all frequencies. The KF is a recursive predictive filter and it uses the state space variables for estimation of the state of the dynamic system. The non-stationary stochastic process is estimated by using statistical method of Minimum Mean Square Error (MSE) criterion. The filter is considered to be a very powerful tool in reducing and controlling the white type of noise (Foss, and Imsland, 2008; Grewal, 2011; Li, 2013; Rullan-Lara, Sergio, and Rogelio, 2011). Under the above assumption and setting, let us consider a system where the process variables such as x_1, x_2,…etc. (or, x, y, …a, w) are represented by a state vector x. Similarly, z is denoted as the observation or measurement vector representing all types of measurements such as z_1, z_2,…etc. (or, x^z, y^z, …a^z, w^z). Fig.2(a) illustrates the interfacing stage and the role of KF. Fig.2(b) illustrates various time steps as the filter estimates the process's state variables.

$$\mathbf{x}=\begin{bmatrix}x_1\\x_2\\x_3\\.\\.\\x_n\end{bmatrix}=\begin{bmatrix}x\\y\\\theta\\v\\a\\\omega\end{bmatrix};\quad \begin{array}{l}\mathrm{x}_k=F\mathrm{x}_{k\text{-}1}\\ \mathrm{x}_k=F\mathrm{x}_{k\text{-}1}+B\mathrm{u}_k\\ \mathrm{x}_k=F\mathrm{x}_{k\text{-}1}+B\mathrm{u}_k+w_k\end{array}\quad;\quad \mathbf{z}=\begin{bmatrix}z_1\\z_2\\z_3\\.\\.\\z_n\end{bmatrix}=\begin{bmatrix}x^z\\y^z\\\theta^z\\v^z\\a^z\\\omega^z\end{bmatrix};\quad \begin{array}{l}z=H\mathrm{x}\\ z_k=H\mathrm{x}_k+v_k\end{array}$$

Where, **u** is input vector, w is the process error or noise with normal distribution, 0 mean, and covariance $\mathbf{Q}_k$, denoted as N(0, **Q**); v, the measurement error or noise, is Gaussian, white, 0 mean, and covariance $\mathbf{R}_k$, denoted as N(0, **R**). Kalman formulated the state of the filter around two variables called estimated state variable, $\hat{\mathbf{x}}_{k/k-1}$ and the error covariance matrix, $\mathbf{P}_{k/k}$. Both are presented here in *a posteriori* form. The covariance represents the estimated accuracy of the state estimates. The filtering process takes two steps: predict stage (*a priori*) and update stage (a posteriori). Under predict stage (i) the process variable, $\hat{\mathbf{x}}_{k/k-1}$ is estimated based on the previous estimate and current measurements, and (ii) the covariance, $\mathbf{P}_{k/k-1}$ is calculated using covariance of the previous time step and the process noise covariance of the current time step. Under update stage (i) measurement residuals, $\tilde{\mathbf{y}}_k$ (ii) covariance of residual, $\mathbf{S}_k$ (iii) Kalman gain, **K** (iv) state estimate for next time step, $\hat{\mathbf{x}}_{k/k}$ and (v) state covariance for the next time step, $\mathbf{P}_{k/k}$ are updated. The following formulations are used in Kalman Filter.

$$\hat{\mathbf{x}}_{k/k-1}=\mathbf{F}_k\hat{\mathbf{x}}_{k-1/k-1}+\mathbf{B}_k\mathbf{u}_k$$

$$\mathbf{P}_{k/k-1}=\mathrm{cov}(\mathbf{x}_k-\hat{\mathbf{x}}_{k/k-1})=\mathbf{F}_k\mathbf{P}_{k-1/k-1}\mathbf{F}_k^T+\mathbf{Q}_k$$

$$\tilde{\mathbf{y}}_k=\mathbf{z}_k\text{-}\mathbf{H}_k\hat{\mathbf{x}}_{k/k-1}$$

$$\mathbf{S}_k=\mathrm{cov}(\tilde{\mathbf{y}}_k)=\mathbf{H}_k\mathbf{P}_{k/k-1}\mathbf{H}_k^T+\mathbf{R}_k$$

$$\mathbf{K}_k=\mathbf{P}_{k/k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1}$$

$$\hat{\mathbf{x}}_{k/k}=\hat{\mathbf{x}}_{k/k-1}+\mathbf{K}_k\tilde{\mathbf{y}}_k$$

$$\mathbf{P}_{k/k}=\mathrm{cov}(\mathbf{x}_k-\hat{\mathbf{x}}_{k/k})=(\mathbf{I}-\mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k/k-1}$$

Where, **F** is called state-transition matrix of the process model, **K** is Kalman Gain, **S** is the residual covariance, and **I** is an identity matrix. The derivation for a posteriori error covariance, shown above, can be seen from (Web reference, Retrived on 2014.6.6).

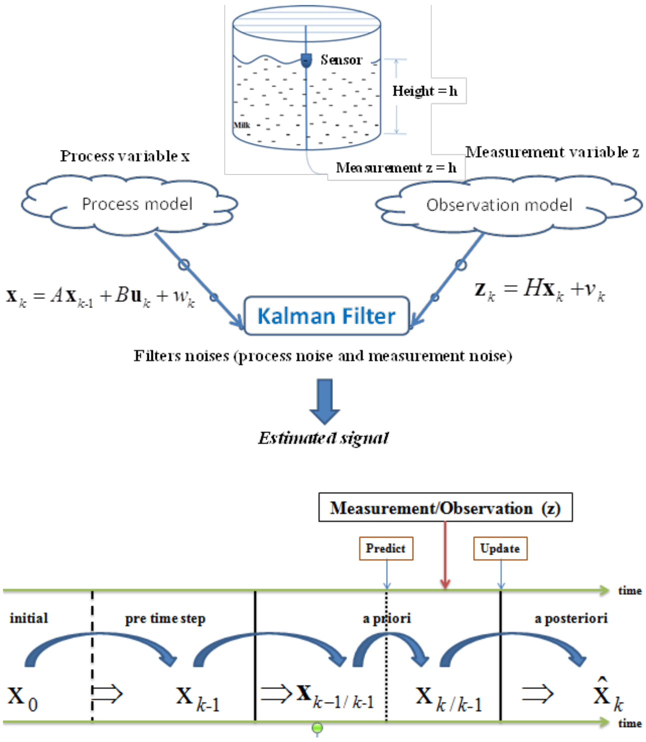


FIG. 2 (Top) THE INTERFACING STSTE AND THE ROLE OF KALMAN FILTER IN THE DYNAMICAL PROCESS; (Bottom) TIME STEPS AND PREDICT AND UPDATE STATE

The behavior of Kalman filter is defined in terms of gain which is a function of the relative certainty of the measurements and current state estimate (Osborn, 2010). The gain is usually tuned to achieve particular performance. Within computation, higher gain refers more inclination toward measurements thereby the estimation follows more closely to each other. On the other hand, a low gain refers more inclination toward model undermining responsiveness but smooth out noise. The extreme ends are 0 and 1 which refer to ignoring of measurements and state estimate (previous time step), respectively. The KF formulation is based on the fact that the relationships between measurements, inputs and state variables are assumed to be all linear. However, the real world process variables and observations are nonlinear in nature.

There are families of KF such as Extended Kalman Filter (EKF), Sigma Point Kalman Filter (SPKF), and Unscented Kalman Filter (UKF) which deal with nonlinearity. Note that while KF estimation is based on MMSE, EKF works around MLE (Maximum Likelihood Estimator). Fig.3 illustrates EKF, SPKF and UKF. In this research we have used linear model of KF formulation (Rached, Ned, and Lars, 1991; Van Der Merwe and Wan, 2001; Jaai, Chopra, Balachandran, and Karki, 2013) .

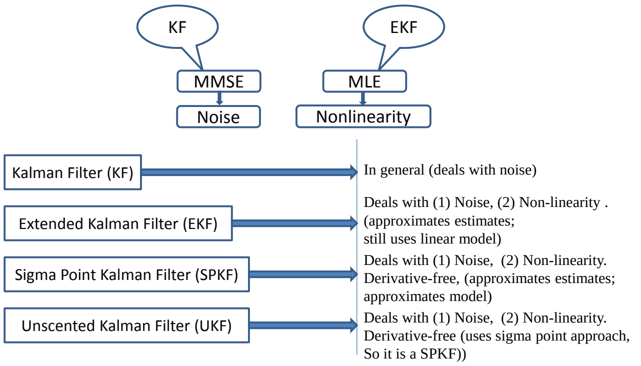


FIG. 3 APPLICATION AREAS OF FAMILY OF KALMAN FILTER

Research Objective and Procedure

This research was conducted in the Collage of Agriculture. Bearing in mind that food and agricultural technology systems are becoming highly automated for which it is imperative to have more and more reliable systems, the research focus was to apply KF technique to reduce process and measurement noises in automated systems in order to improve reliability. A system can be a yield monitoring system, humidity measurement system for frost control application, or similar applications as seen in the agricultural operations.

Accurate measurement of water level is crucial in tanks that are used for aquaculture applications. Also in the agricultural areas where water scarcity is high precise measurement of water level in the storage puns plays vital role. Note that in Central California usage of water is critical. This research is motivated by the fact that a significant percentage of water is stored in tanks, standalone ponds or reservoir, and interconnected ponds where precise height measurement methods are essentially plays vital role due to the reason that the process of filling up such tanks or ponds are carried out automatic control. In this research, although, the developed algorithm was tested in a lab setting, it can be embedded into existing height measuring devices or sensors for feedback solution and integrated with SCADA (Supervisory Control and Data Acquisition) backbone for remote monitoring and control along with irrigation application (Ko, Kim, Mahalik, and Ryuh, 2013; Mahalik and Kim, 2014; Gunasekaran, Kannan, and Mahalik, 2013) .

Similarly, autonomous vehicles (AV) are being used in agricultural applications. Some of the important applications of AVs are crops monitoring, field mapping, soil sampling, pesticide spraying, and so on. This type of mechanized mobile robot uses navigation measurement system (NMS) as one of the main functional unit. At the lowest level, an LVDT can be considered as one of the primitive unit to accomplish the task. As an example, LVDT embedded with a KF algorithm will be able to reduce the process and measurement noise so as to enable the robotic system to perform the spraying operation with higher degree of accuracy in following the predefined path.

Kalman Filtering (KF) method was used to estimate the process and measurement noises in Apollo exploration. However, because of the advent of low-cost high performance computer chip and electronic measurement modules, the KF method can be applied in any automated systems requiring higher reliability in operation. Through this research study, we have accomplished the following.

- Studied the KF framework and correlate the functional algorithm. The review is reported in the previous section.
- Developed, tested and validated the KF algorithm using MATLAB software (see the following section.).
- Transferred the algorithm to the electronic measurement board integrated with temperature, water level sensor, and LVDT (Linear Variable Differential Transducer, a tracking sensor used in navigation of mobile robot)

Most of the food processing and agricultural operations use temperature sensors and water level detectors. A simple pressure sensor (level detector) was used for the verification and validation of the developed algorithm. The sensor was used to sense the height of the real-time water level in a lab room experimental setting. Note that precise height measurement methods plays vital role in agriculture due to the reason that the processes of filling up tanks or ponds are carried out automatically. Similarly, mobile robotic systems are currently being used to spray pesticides on the row plant (Shashank, Nitin,

Rakshith and Alamelu, 2012). The mobile robot uses navigation measurement system as one of the main functional unit. We have selected LVDT sensor as a typical navigation measuring unit. We implemented KF in order to reduce the error or noise so that the robot can navigate more accurate path and perform the spraying operation with higher coverage of leaves as desired.

Results

Class-room based MATLAB software was used to develop the algorithm. MATLAB is widely used because the built-in math functions enable to explore several approaches and reporting results. MATLAB also includes GUI (Graphical User Interphase) environment for solutions of graphical in nature. The execution and error checking process is very easy due to the availability of help tools and descriptions. Since the computations are done in matrix and vector calculus, the results are very exact. The tools in the MATLAB enable to create better program with high graphics. We developed code in MATLAB what was residing in a PC type computer. The algorithm was first validated in MATLAB via simulation. It was then translated to microcontroller platform compatible to neuron C language for real-world testing. The microcontroller platform that we used for this implementation is a fieldbus system called LonWorks Technology. As mentioned, a PC was used to interface the microcontroller module integrated with the sensors.

After the filter is defined, code is developed and testing is performed. The algorithm was tested by providing initial values to the filter. Assuming the water level is constant, the initial level was chosen as 1. The initial values of the process variables and process error covariance should be minimum and maximum, respectively. At the beginning, we need to believe that the process variables are not visible for which the error covariance was maximum. We have to check whether or not the filter will eliminate our wrong belief. Under this condition, we initialize x0 = 0, P = 500, Q = 0.001, and y = 0.90. Then we have measurement noise r = 0.10 [20]. The values of measured, estimated and various covariance of the system up to time step 7 are shown in Table 1. The results (Table 1 and Fig.4) show that although the measurements fall within the 15% of the real value the estimated value via KF is within 2-5% of the true value. The plot he level of water on y-axis and time scale on x-axis, we can observe how estimated value is close to the true value.

TABLE 1 USE OF KALMAN FILTER FOR SIMULATION

t	$x_{t/t-1}$	$P_{t/t-1}$	y_t	K_t	$x_{t/t}$	$P_{t/t}$
1	0	500.001	0.9	0.9998	0.8998	0.10001
2	0.8998	0.10101	0.8	0.5025	0.8496	0.0503
3	0.8496	0.0513	1.1	0.3347	0.9334	0.0341
4	0.9334	0.0523	1.15	0.3434	1.008	0.0343
5	1.008	0.0353	1.2	0.2609	1.0581	0.02609
6	1.0581	0.02709	0.95	0.21315	1.0351	0.0213
7	1.0351	0.2230	0.85	0.1823	1.0013	0.01823

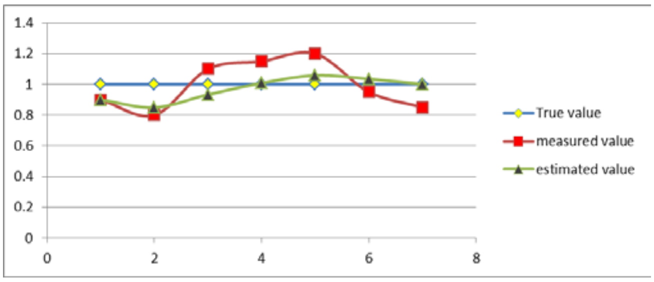


FIG. 4 SIMULATION BASED ILLUSTRATION OF KALMAN FILTER (ESTIMATION VS. TRUE VALUE)

The algorithm was transferred to the NodeBuilder development platform and the code was re-written using Neuron C language. The level sensor was interfaced with the I/O module as illustrated in Fig.5.

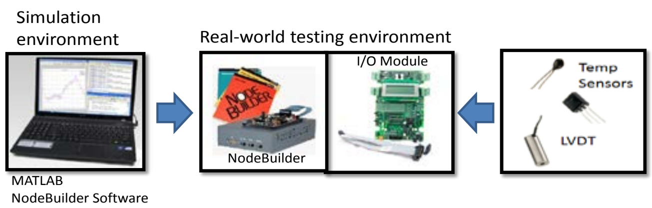


FIG. 5 METHODS AND PROCEDURE

A bucket of water was placed on a mechanical simulator plate. And the amplitudes of the simulation were defined. Depending upon the amplitude of vibration the errors were this manually introduced. The amplitudes can be fixed or incremental. Under this condition, several experiments were conducted. As can be seen from Fig. the estimated value is closer to the true value when compared to the measured value. We also considered a scenario where the water in the tank is sloshing but a filling at a constant rate.

The sensor that is used to measure the level of water is a pressure transducer with data logger. It can measure the level of water above 1ft. The transducer used in the sensor can measure the pressure and converts to height of the water. In this work we used millivolt output pressure transducer. The output of the millivolt pressure transducer directly depends on the excitation and the nominal output is about 30 millivolts.

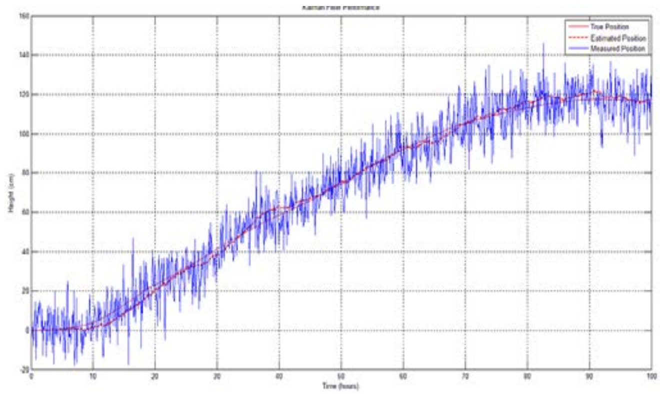
Fig.6(a-c) shows the results based on the conducted three experiments: water level increasing, dropping,

and both. The graph shows the level of water on y-axis with respect to time in x-axis. We made arrangement to allow water level to increase with variable rate in a slow rate filling process and then allow the level become steady. The noise in the process is high when it is compared to the quicker dropping rate. In all scenarios, KF reduces the noise and produces a less noisy signal at the output of the sensor. The observations and the measured values were processed via KF algorithm and the results shows that even with 14% error, the estimated value lies within 3% of the true value. It can be clearly observed that the estimated values are precisely close to the true values in all these three situations, eliminating the process and measured noise.

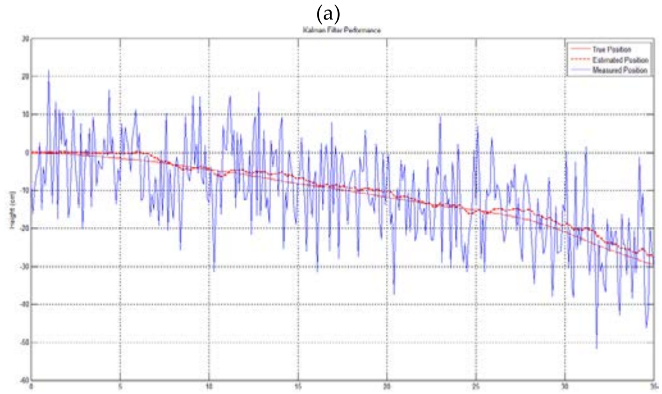
Kalman Filter in Mobile Robot Navigation

An LVDT sensor was retrofitted with a Mobile Robot (MR) platform as shown in Fig.6. A path pattern was defined and the MR was programmed to follow the path pattern in real time. The KF algorithm was embedded into the LVDT sensor using NodeBuilder development tool. Without KF the robot was able to follow the path pattern; however the amount of deviation from the track was significant.

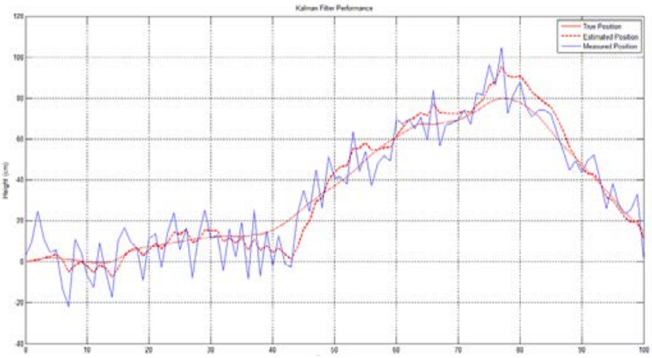
The LVDT integrated robot navigation works as follows. LVDT provides a differential signal if the robot is out of rack. There are three situations that can be noted. If the robot is navigating along the right side of the guided navigating track, for example, the LVDT will produce a positive differential voltage signal and if the robot is navigating along left side of the track it produces negative differential signal, and if the robot is exactly on the middle of the track, the differential voltage is zero. Thus, the LVDT performed as a feedback sensor. Based on the amplitude and polarity of differential voltage the robot autonomously adjusts itself to appropriately navigate along the path. This is



(a)

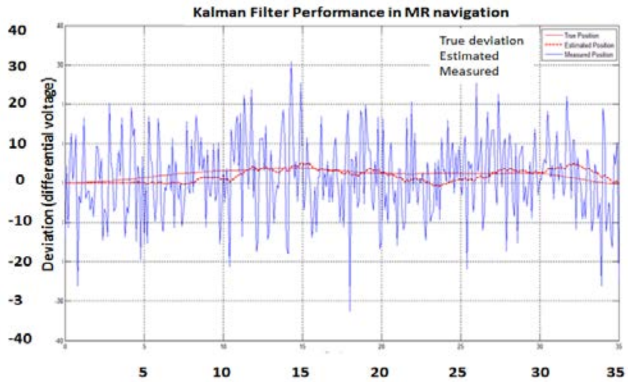


(b)



(c)

(d)



(e)

FIG. 6 (a) WATER FILLS AT CONSTANT RATE; (b) DROPS AT CONSTANT RATE; (c) FILLING AND DROPPPING SITUATION; (d) MOBILE ROBOT (FROM ADEPT INC.) USED IN THIS EXPERIMENT; (e) TRACKING ESTIMATION VIA DETECTIN OF ANGLE BY THE USE OF LVDT SENSOR FOR MOBILE ROBOT NAVIGATION

the procedure how a MR usually navigates along a tracked line. The tracked line is usually powered electromagnetically (RF signal). LVDT is a kind of transformer which induces voltage when it is kept reasonably close to the live RF signal line. The RF signal was provided from a laboratory based the Function Generator. The received voltage is usually very small for which an amplifier is needed to bring the LVDT's differential voltage to a workable level. The LVDT and the amplifier were developed in the laboratory. LVDT basically has three coils (one primary and two secondary coils) coiled using available magnet wires (AWG#28 was used) with a common core (soft iron). The calibration of LVDT was performed prior to using it in the MR platform as a feedback sensor. The MR was programmed to navigate at variable speeds 3 in/s to 80% of its maximum speed limit. Fig. 7 shows the results. The robot was more accurately followed the true path apttern.

Conclusion

In this work we present experimental results by using Kalman Filter (KF) in order to reduce the process and measurement errors and noise. First, we reviewed the KF and its formulation. The review also mentions some of the important assumptions to be made. The requirement is that the underlying system has to be a linear dynamical system. Other important aspect of use of Kalman Filter is that it works when the process variables distribution is Gaussian. Also, the filter assumes the noise is white. In the experiment, the algorithm produces estimates. The estimation is precise because the filtering process involves multiple measurements. The computation is a two-steps phase: prediction step where the filter algorithm produces estimates of the current state, along with the uncertainty and the update step where it gets updated using a weighted average. More weight is given to estimates with higher certainty, an inherent formulation of the filter. Because, the filter runs in real-time where inputs and measurements and received during run-time, no past information is necessary.

We then implemented the KF algorithm in two scenarios: open loop and closed loop. While the open-loop system was a simple level detector to measure the level of water in a tank, the closed-loop system was a Mobile Robot (MR) platform integrated with LVDT sensor. The LVDT was used to measure the deviation of angle when the MR was not appropriately following the path pattern. Prior to translating the KF algorithm to the computing and data-logging platform for real-world practical observation, we tested the algorithm through simulation. Within the simulation environment, we concluded that if the system and noise are modeled appropriately, the filter can work outstandingly. From the results, we can clearly conclude that the KF technique will be able to successfully reduce the process and measurement noise. It was observed that with about 15% error in the measured values, the algorithm was capable of reducing it to 5% range.

While we focus on general form of Kalman Filter that is applied to linear system, our future work will include using EKF and UKF applicable to nonlinear systems. We assumed that a constant speed MR navigation system is relatively a linear system. If the variable speed navigation strategy is implemented the process can be considered as a nonlinear process because of inherent shaking and backlash that may occur during acceleration and deceleration or when the MR changes speed while navigating.

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